This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2018.2794615, IEEE Transactions on Industrial Informatics

Space-Reserved Cooperative Caching in 5G Heterogeneous Networks for Industrial IoT

Peng Duan, Yunjian Jia, *Member, IEEE*, Liang Liang, Jonathan Rodriguez, *Senior Member, IEEE*, Kazi Mohammed Saidul Huq, *Member, IEEE*, and Guojun Li

***Abstract*—The large amount of data amongst billions of devices deployed for Industrial Internet of Things (IIoT) cause a massive energy consumption. Driven by the pursuit of green communication, this paper presents a space-reserved cooperative caching scheme for IIoT in the 5th generation (5G) mobile heterogeneous networks, where the cache space in a base station (BS) is divided into two parts, one is used to store the prefetched data (PFD) from the servers ahead of the device request time and the other is reserved to store the temporarily buffering data (TBD) in the wireless transmission queue at the device request time. With the constraint that the quality of service is guaranteed, we propose an algorithm to obtain the optimal proportion between the two parts of the caching space for the purpose of reducing the average energy consumption. Simulation results verified that the proposed caching scheme is more efficient than the conventional one with respect to the average energy consumption.**

***Index Terms*—Cooperative caching, space-reserved, energy consumption, Industrial Internet of Things (IIoT), 5G.**

I. Introduction

Mobile Internet and the Internet of Things (IoT) are two main drivers for the 5th generation (5G) mobile networks [1]. Looking ahead to 5G and beyond, the unprecedented services and application scenarios especially Industrial Internet of Things (IIoT) is facilitating hundreds of billions of devices connected to the networks [2]–[3]. Meanwhile, the explosive growth of mobile data will consume a mass of energy, which has become an important issue that needs to be urgently addressed. To reduce energy consumption, caching has been proposed as a promising technology [4]–[6]. Since dense small base stations (SBSs) are expected to be deployed to support the IIoT, the SBSs can prefetch data from the servers.

Manuscript received September 30, 2017; revised December 9, 2017; accepted December 17, 2017. This work was supported in part by the Scientific Research Foundation of the Ministry of Education of China-China Mobile under Grant No. MCM20150102; in part by the National Key Research and Development Program of China under Grant No. 2016YFE0121100; in part by the Program for Innovation Team Building at colleges and universities in Chongqing, China under Grant No. CXTDX201601006; in part by the National Natural Science Foundation of China under Grant 61601067; and in part by the Natural Science Foundation of Chongqing under Grant Cstc2015jcyjBX0078.

Peng Duan, Yunjian Jia, and Liang Liang are with College of communication engineering, Chongqing University, 400044 Chongqing, P. R China. (e-mail: duanpeng, yunjian, liangliang@cqu.edu.cn) [Corresponding Author:Yunjian Jia].

Jonathan Rodriguez is with the Instituto de Telecomunicações, Aveiro, Portugal and the University of South Wales (UK). (e-mail: jonathan@av.it.pt)

Kazi Mohammed Saidul Huq is with the Instituto de Telecomunicações, Aveiro, Portugal. (e-mail: kazi.saidul@av.it.pt)

Guojun Li is with Chongqing University of Posts and Telecommunications, 400065 Chongqing, P. R China. (e-mail: skywavecommnavi@126.com)

IIoT make it possible for industrial devices to have Internet connection and share data. Huge amount of data are collected or analyzed in the cloud servers, the meaningful data would be extracted as "services". The feature of these services is that a same copy of data may be needed by multiple devices. For example, in the scenario of smart city, when people drive cars through the city or wander in the street of the city, if they want to download something like music or videos, they can get the data in the SBSs which have cached the corresponding data. Another scenario is smart environment. The information about air, water would be collected by monitoring system, then, the measurements are sent to cloud servers to analyze. If the feedback data from the cloud servers are pushed to the SBSs in advance, when people especially those who have the desire of analyzing and managing environmental resources want to know the quality of the environment, then, the requested data can be promptly retrieved in the SBSs. Therefore, instead of fetching the data from the servers in the remote site, lots of data requests can be satisfied by caching data at the SBSs, i.e., local caching, and the energy consumption caused by wired routing from the severs to the SBSs is cut down [7].

Caching attracted many interests in the academic and industry areas, and several studies with respect to caching have been discussed in the existing works. Some typical caching scenarios have been introduced and discussed in [8] and enabling research directions for caching in wireless systems are uncovered in [9]. The main differences between wired and wireless caching are discussed in [10]. In [11], authors propose a PHY-caching scheme for 5G wireless networks to improve the spectral efficiency. In [12], authors propose an architecture allowing different networks, multiple interfaces, and in-network caching be leveraged effectively by mobile devices. In [13], authors propose a novel framework that considers joint networking, caching and computing techniques in a systematic manner. In [14], authors present an alternative framework for mobile systems in which communications, caching and computing are identified as the three primary resources. Coded caching scheme has been proposed for single bottleneck caching network in [15]–[17]. Since the movement of users changes the topology of networks and the optimal solution of caching placement changes over the time, the authors model users' mobility as a discrete Markov chain in [18], and in [19], authors study the issue of mobility-aware content caching. The joint routing and caching problem has been considered in [20], aiming to maximize the fraction of content requests served locally by the deployed SBSs. The average delay of cache-enabled cell network based on queuing

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2018.2794615, IEEE Transactions on Industrial Informatics

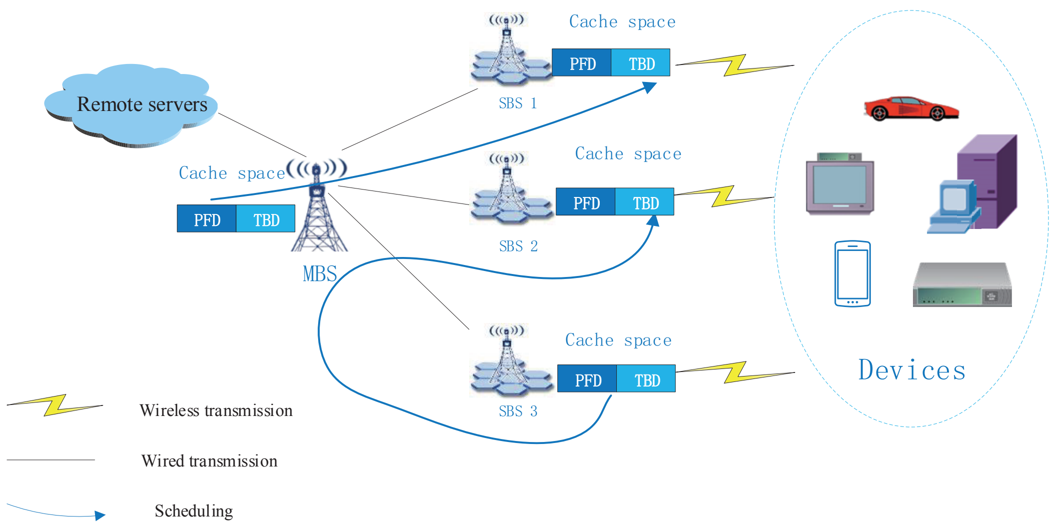


Fig. 1. Cooperative caching in 5G heterogenous networks for IIoT.

theoretical approach is analyzed in [21]–[22]. Authors discuss about the energy-efficient caching and delay of caching in heterogeneous cellular networks in [23] and [24], respectively.

Aforementioned works are based on no-cooperative caching mechanisms. To further improve the efficiency of caching, cluster based caching methods are presented in [25]–[28]. In particular, [25] proposes a joint clustering and caching scheme for wireless small cell networks. An adaptive cluster-centric small cell network with cooperative caching and transmission design is further introduced in [26], and caching placement algorithms for offloading the heavy traffic from the wireless network are studied in [27]. Authors in [28] present a content-centric transmission design in a cloud radio access network by the combination of multicasting and caching. Energy saving in cellular systems is increasingly important for green communication, some related works about heterogeneous networks with content caching for energy-efficiency are studied in [29]–[34]. The cache-enabled wireless heterogeneous networks with the control-plane (C-plane) and user-plane (U-plane) splitting are proposed in [29], and the activation policy with the caching policy for green heterogeneous cellular networks is studied in [30]. Optimizing the place-then-transmit strategy for energy-aware multicell cooperation in HetNets with content caching is described in [31]. Authors design an effective push mechanism of energy harvesting powered SBSs in heterogeneous networks in [32]. Moreover, the advantage of encoding the data using maximum-distance separable (MDS) codes over the alternative concept of file fragmentation with respect to both backhaul rate and energy consumption is shown in [33], an algorithm is proposed in [34] to reassign UEs to eNBs to minimize the total energy consumption of UEs with the constraint that their throughput is guaranteed.

However, almost all papers only consider the cache space for caching data ahead of the device request time in the BSs. In fact, the cache space for buffering data at the device request time in the BSs is existed. Therefore, the joint optimization the two kinds of cache space remains unexplored.

Motivated by the above observations, we propose a space-reserved cooperative caching scheme for IIoT in 5G heterogeneous networks to reduce the systems average energy consumption. The word "space-reserved" means that the cache space in the BSs is not fully used to store the prefetched data from the servers ahead of the device request time, and a small proportion of cache space would be reserved as buffer for wireless transmission. Then, when the data requested by devices not have been cached in the local caching, the cooperative BSs could schedule the corresponding data to the reserved space of the serving BS, and the scheduled data meet the demands of the devices through wireless transmission. Specifically, we consider the scenario that neighboring SBSs could establish cooperative relationship through macro base station (MBS). Caching is configured at BSs (SBSs and MBS) and the data cached in the BSs can be exchanged via the MBS as relay in the considered cooperative caching scheme. In this case, the data requested by devices have been already cached in corresponding local BS, and the local BS can transmit the data directly. Otherwise, the local BS needs to fetch the data from other neighboring cooperative BSs or fetch from the servers via backhaul links. Based on the space-reserved cooperative caching method, the cache space in a BS is divided into two parts, one is used to store the prefetched data (PFD) from the servers ahead of the device request time and the other is reserved to store the temporarily buffering data (TBD) in the wireless transmission queue at the device request time. Obviously, the optimal proportion between the two parts should be determined for minimizing the energy consumption. We comprehensively consider the energy consumption of wireless transmission, wired transmission (we only consider wired transmission between servers and BSs), scheduling data, and maintaining caching to seek the lowest average energy consumption.

The main contributions of this paper can be summarized as follows:

1) Proposing a novel cooperative caching scheme for IIoT in 5G heterogeneous networks: We utilize small reserved cache space for data sharing among BSs in the cluster to

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2018.2794615, IEEE Transactions on Industrial Informatics

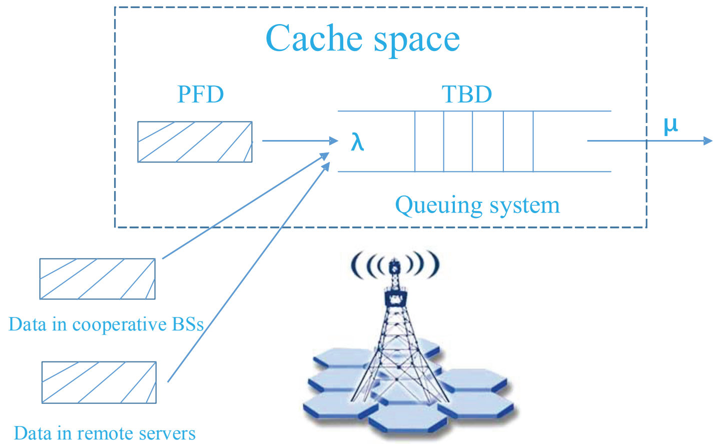


Fig. 2. Queue model.

improve the caching efficiency.
2) Exploring the optimal allocation proportion between the two parts of the cache space of the BSs to obtain the minimal average energy consumption.
3) Providing comprehensive simulations to evaluate the performance of the proposed caching scheme and getting some important conclusions.

The rest of the paper is organized as follows. Section II describes the structure of the cooperative caching in 5G heterogeneous networks for IIoT and gives the system model and assumptions. Section III formulates the mathematic model and analyzes the minimal average energy consumption. Gold section algorithm is presented in Section IV. Section V gives the results of simulations and we conclude the paper in Section VI.

II. System Model and Assumption

A. System Model

As shown in Fig.1, we assume that N SBSs and one MBS exist in the cooperative heterogeneous networks, where the MBS can control the data exchange among the BSs. Caching is configured at each BS with overall capacity of cache space C. The cache space in a BS is further divided into two parts, one is used for PFD and the other is reserved for TBD. The connections between MBS and servers are wired, and the same with the connections between SBSs and MBS. While the devices connect to BSs through wireless links. For simplicity, we ignore the interference in the system model. As we focus on the study of cooperative caching scheme, ignoring the interference does not have essential impact on the design, execution and performance evaluation of our scheme. In other words, our scheme can be applied in the interfering scenario with only a different computational complexity. Besides, some related works (such as [35]) do not consider interference for analyzing and simulation.

The request processes of devices served by the SBSs are as follows:

1) When the data requested by devices have been cached in the serving SBS, then the local SBS can response directly to satisfy the demands of the devices.
2) When the serving SBS does not cache the requested data, the SBS first seeks the data from the corresponding MBS. If the MBS has cached the required data, the data would be firstly transferred from the MBS to the local SBS, then delivered to devices.
3) When the MBS also does not cache the data, the MBS seeks from other cooperative SBSs. If the data have been cached in other SBSs, the data would be firstly transferred to the MBS, then delivered to the local SBS. The devices finally can get the data from the local SBS through the wireless transmission.
4) When all the BSs in the cluster do not have cached the data, it is necessary to get the data from the servers via backhaul links.

The request processes of devices served by the MBS are as follows:

1) When the data requested by devices have been cached in the serving MBS, then the local MBS can response directly to satisfy the demands of these devices.
2) When the serving MBS does not cache the requested data, the MBS seeks the data from the cooperative SBSs. If a SBS has cached the required data, then the data would be firstly transferred from this SBS to the MBS, then delivered to devices.
3) When the other cooperative SBSs do not have cached the data, it is necessary to get the data from the servers via backhaul links.

B. Wireless Transmission Model

We assume that the wireless bandwidth is B Hz. To simplify the model, both BSs and devices work in single-antenna mode, thus each BS can serve at most one device at any moment. Nevertheless, the model can be easily extended to multi-antenna scenario. We denote transmitting power from BS to device i as P_i, and the Gaussian white noise is denoted as σ^2. The channel gain from BS to device i which is in its coverage as g_i, and the channel gain from an arbitrary BS to the devices beyond its coverage is 0. We define the wireless transmission rate of device i is R_i, the size of each data set is L bits and the

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2018.2794615, IEEE Transactions on Industrial Informatics

wireless delay is D seconds. Then, according to the Shannon capacity formulation, we have

$$R_i = B\log_2(1 + \frac{P_i g_i}{\sigma^2}) = \frac{L}{D}. \quad (1)$$

We can further deduce

$$P_i = (2^{\frac{L}{BD}} - 1)\frac{\sigma^2}{g_i}. \quad (2)$$

We assume that the energy consumption of wireless transmission for one data set is E_1, then the energy consumption of wireless transmission for the device i can be calculated as

$$E_{1i} = P_i D = (2^{\frac{L}{BD}} - 1)\frac{\sigma^2}{g_i}D. \quad (3)$$

Hence, the wireless transmission delay D is an important parameter to calculate the energy consumption of wireless transmission. We can use the knowledge of queuing theory to get the optimal value of D. Assuming that the proportion between the cache space for PFD and the cache space for TBD is $(1-\alpha)$:α, where $\alpha \in (0,1)$. To guarantee the quality of service, a smaller α leads to faster wireless transmission as well as a smaller D, and vice versa. We assume that λ is the arriving rate of service, μ is the serving rate of each BS, ρ is service intensity. As shown in Fig. 2, Q is the length of waiting queue in the cache space for TBD, and the data to be transmitted in the queue are from the local caching, the cooperative BSs and the servers. According to the M/M/1 queuing theory in [36], we can have the delay d in the queuing system

$$d = \frac{1}{\mu - \lambda}, \quad (4)$$

where $\mu > \lambda$, in order to maintain the stability of the queuing system. According to μ and λ, the service intensity is the ratio of the arriving rate to the serving rate, then we can easily get the service intensity ρ

$$\rho = \frac{\lambda}{\mu}. \quad (5)$$

Once we get the service intensity ρ, we can further get the length of waiting queue Q, which expresses how many data are buffered temporarily in the cache space for TBD

$$Q = \frac{\rho}{1-\rho}. \quad (6)$$

The data buffered temporarily in the cache space for TBD should not exceed the capacity allocated for TBD, then Q should meet

$$Q \leq C\alpha. \quad (7)$$

Then, according to (4)–(7), we can further derive

$$d \leq \frac{C\alpha}{\lambda}. \quad (8)$$

It has proved that if the interference between BSs is ignored, the wireless energy consumption can be minimized when wireless delay is maximized [35]. Since the delay of wireless transmission D is not exceeding the delay in the queuing system d, to get the minimal wireless energy consumption, we let

$$D = \frac{C\alpha}{\lambda}. \quad (9)$$

Then we can rewrite (3) as

$$E_{1i} = \frac{(2^{\frac{L\lambda}{BC\times\alpha}} - 1)\sigma^2 C\alpha}{g_i \lambda}. \quad (10)$$

If there are K devices in a cluster, the average energy consumption of wireless transmission for each device is expressed as

$$E_1 = \sum_{i=1}^{K} \frac{E_{1i}}{K}. \quad (11)$$

C. Scheduling Model

Once the data requested by devices are cached in local serving BSs, the data can be directly transmitted from the BSs, then the wired transmission is omitted.

When the requested data of devices served by the SBSs have not been cached in the local SBSs, the demanded data would be firstly searched from the corresponding MBS. If the MBS has cached the requested data, it does not need to get the data from the servers, and the wired transmission is omitted too. However, there will be extra energy consumption of scheduling data from the MBS to local SBS. We assume that the total number of data sets needed by devices is F, then the devices arbitrarily request one data set, the probability of scheduling data from MBS is expressed as p_1

$$p_1 = \frac{C(1-\alpha)}{F}. \quad (12)$$

If the MBS has not cached the data, it would seek data from other cooperative SBSs. When the data have been cached in other SBSs, the data would be firstly transferred to the MBS, then delivered to the local SBS, the devices finally can get the data through the wireless transmission of the local SBS. Although the wired transmission is omitted, energy will be consumed when scheduling data from other SBSs to the local SBS. The probability of scheduling data from other cooperative SBSs is expressed as p_2

$$p_2 = \frac{(N-1)C(1-\alpha)}{F}. \quad (13)$$

When the requested data of devices served by the MBS have not been cached in the local MBS, the demanded data would be searched from other cooperative SBSs. If other cooperative SBSs have cached the requested data, the wired transmission is omitted and only need less extra energy consumption of scheduling data from a SBS to the MBS. If the devices arbitrarily request one data set, the probability of scheduling data from other cooperative SBSs is expressed as p_3

$$p_3 = \frac{NC(1-\alpha)}{F}. \quad (14)$$

We assume that the energy consumption of scheduling one data set between MBS and SBS is e_1. When the data requested by devices are from the cooperative BSs, the extra energy consumption of scheduling is also needed. Let the average

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2018.2794615, IEEE Transactions on Industrial Informatics

energy consumption of scheduling for requesting one data set be E_2 and it is expressed as

$$E_2 = (p_1 e_1 + 2p_2 e_1)\frac{N}{N+1} + p_3 e_1 \frac{1}{N+1}. \quad (15)$$

D. Wired Transmission Model

Since the capacity of each BS is limited, it is impossible to satisfy all requests in the cooperative BSs cluster. When all BSs in the cluster do not cache the data, it is necessary to get the corresponding data from the servers. The probability of devices getting the data from the servers is expressed as p_4

$$p_4 = 1 - \frac{(N+1)C(1-\alpha)}{F}. \quad (16)$$

We assume that the energy consumption of wired transmission for one data set is e_2. If the data requested by devices are from the servers, except the energy consumption of wireless transmission, the extra energy consumption of wired transmission is also needed. Let the average energy consumption of wired transmission for requesting one data set be E_3 and it is pressed as

$$E_3 = (1 - \frac{(N+1)C(1-\alpha)}{F})e_2. \quad (17)$$

E. Caching Model

Indeed, when the data cached in the BSs, energy is needed to maintain its operation. We assume that the average energy consumption of maintaining each data set for devices getting one data set is e_3, and the average energy consumption of maintaining all data sets of the BSs cluster for devices getting one data set is E_4, then E_4 is expressed as

$$E_4 = (N+1)C(1-\alpha)e_3. \quad (18)$$

III. Problem Formulation and Analysis

The energy consumption incurred by the wireless transmission from the serving BS to the devices is needed, and the received data of devices have three sources, they are the local caching, the caching in other cooperative BSs and the servers. It is reasonable that the energy consumption is lower if the requested data are fetched from a place that is closer to the devices. When the data received from the local caching, the energy consumption E_1 in wireless transmission is needed, otherwise, extra energy will be consumed. If the data received from the caching of other cooperative BSs, extra energy will be consumed by scheduling. If the data received from the servers, extra energy will be consumed by wired transmission. As discussed in Section II, the average energy consumption of scheduling for requesting one data set is E_2 and the average energy consumption of wired transmission for requesting one data set is E_3, then, when the device obtains its desired data, the average energy consumption for requesting one data set is $E_1+E_2+E_3$. However, when caching has been introduced in the BSs, the energy consumption of maintaining all data sets of the BSs cluster for getting one data set is E_4. Therefore, the energy consumption actually consists of four parts, they are the energy consumption of wireless transmission, the energy consumption of wired transmission, the energy consumption of scheduling and the energy consumption of maintaining caching. We assume that the average energy consumption for requesting one data set is E, then we can get

$$E = E_1 + E_2 + E_3 + E_4. \quad (19)$$

We aim to search for the optimal α to minimize the average energy consumption E. Thus the problem can be formulated as

$$\min_{\{\alpha\}} E \quad (20)$$

subject to:

$$\lambda < \mu \quad (21)$$

$$Q + (1-\alpha)C \leq C \quad (22)$$

$$\alpha \in (0,1) \quad (23)$$

We can further get the expression of the average energy consumption E according to (10)–(19)

$$\begin{aligned} E = &\sum_{i=1}^{K} \frac{(2^{\frac{L\lambda}{\alpha BC}} - 1)\sigma^2 \alpha C}{g_i \lambda K} + \frac{2(1-\alpha)CN^2 e_1}{F(N+1)} \\ &+ (1 - \frac{(N+1)C(1-\alpha)}{F})e_2 + (N+1)C(1-\alpha)e_3. \end{aligned} \quad (24)$$

As discussed above, a smaller α leads to larger energy consumption of wireless transmission at BS end, and a larger α renders larger probability of getting data from the servers, leading to much energy consumption of wired transmission. Therefore, we should first determine the tradeoff factor α, in order to minimize the average energy consumption. The first order partial derivative of E with respect to α is

$$\begin{aligned} E'(\alpha) = &\sum_{i=1}^{K} (2^{\frac{L\lambda}{\alpha BC}} - 1)(1 - \frac{\ln 2L\lambda}{\alpha BC})\frac{\sigma^2}{K g_i} \\ &+ \frac{e_2(N+1)C - (N+1)CFe_3}{F} - \frac{2N^2 C e_1}{F(N+1)}. \end{aligned} \quad (25)$$

The second order partial derivative of E with respect to α is

$$E''(\alpha) = \sum_{i=1}^{K} (2^{\frac{L\lambda}{\alpha BC}} - 1)\frac{\sigma^2(\ln 2L\lambda)^2}{g_i \alpha^3 K (BC)^2}. \quad (26)$$

We can see that $E''(\alpha) > 0$, then E is a concave function with respect to α.

Algorithm 1 Gold section algorithm for solving (24)

1) **Initialize**: k=1, a_1=0, b_1=1, $L = 10^{-3}$;
2) Let $\lambda_1 = a_1 + 0.382(b_1 - a_1)$, $\mu_1 = a_1 + 0.618(b_1 - a_1)$;
3) **If** $b_k - a_k < L$, then $\alpha = a_k$;
4) **Else if** $E(\lambda_k) > E(\mu_k)$, then go to step 6;
5) **Else** $E(\lambda_k) \leq E(\mu_k)$, then go to step 7;
6) $a_{k+1} = \lambda_k$, $b_{k+1} = b_k$, $\lambda_{k+1} = \mu_k$, $\mu_{k+1} = a_{k+1} + 0.618(b_{k+1} - a_{k+1})$, caculate $E(\mu_{k+1})$, and go to step 8;
7) $a_{k+1} = a_k$, $b_{k+1} = \mu_k$, $\mu_{k+1} = \lambda_k$, $\lambda_{k+1} = a_{k+1} + 0.382(b_{k+1} - a_{k+1})$, caculate $E(\lambda_{k+1})$, and go to step 8;
8) $k = k+1$, go back to step 3;
9) **End if**.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2018.2794615, IEEE Transactions on Industrial Informatics

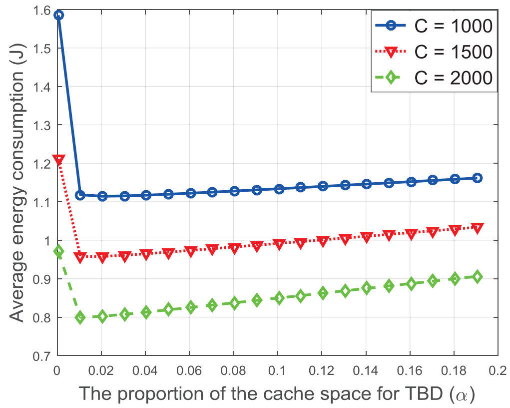


Fig. 3. The relationship between E and α.

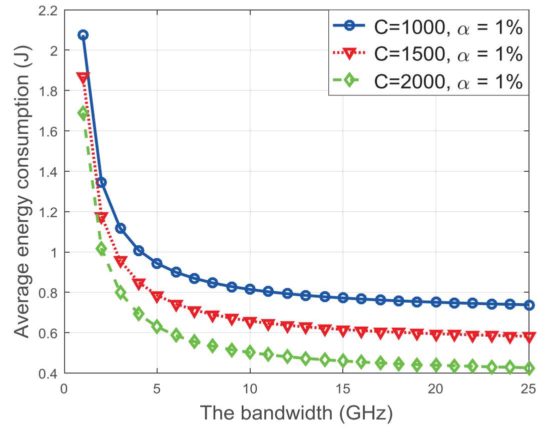


Fig. 4. The relationship between E and B.

IV. Solution Algorithm

Since the objective function is one-variable real function, and the objective function E is a concave function with respect to the variable α, so the objective function E must have the minimal value, and the variable's value of obtaining the minimal value of function is unique. To search for the minimal value of the average energy consumption E, the golden section algorithm is suitable for solving the problem as in Algorithm 1. According to the basic idea of golden section algorithm [37], we continuously narrow the interval that contains the minimal point through choosing tentative points λ_k and μ_k. When the interval is enough narrow, the value of function of each point in the interval is lose to the minimal value of function, then we can choose any point as the minimal point, so the algorithm is convergent. We can also notice that, except for the first iteration, we only need to choose one tentative point in each iteration, the computational complexity is reduced.

V. Simulation

In this section, we provide comprehensive simulations to verify the effectiveness of the proposed caching scheme. Simulation parameters are given in Table 1. We assume that the BSs and devices work in the single antenna mode, and the devices can only be directly served by one BS.

A. The Impact of α

We should first get the optimal α to achieve the minimal average energy consumption for obtaining one data set. In Fig. 3, when α is relatively small, the capacity allocated for TBD is limited. This leads to faster wireless transmission for guaranteeing the quality of service, and massive energy consumption for wireless transmission. As α increases, the amount of power consumed decreases. However, if α further increases, there is less cache space for PFD, and the BSs cache less data. Then, the amount of scheduled data from other BSs and the data from the servers both increase. Therefore, the energy consumption in scheduling and wired transmission correspondingly increases. As shown in Fig. 3, when $\alpha = 1\%$, the average energy consumption achieves its minimal value.

Another observation in Fig. 3 is that when the total capacity of cache space C enlarges, the system average energy consumption decreases. This is because that more amount of data can be cached in the local BS. Then less data need to be scheduled from other BSs or gotten from the servers. The energy consumption of scheduling and energy consumption of wired transmission are omitted.

The third observation in Fig. 3 is that the value of α achieving the minimal average energy consumption basically maintains at $\alpha = 1\%$. According to (9), we can see that α should be held at a certain level to guarantee the enabled wireless delay for decreasing the wireless energy consumption.

TABLE I
Simulation Parameters

Parameters	Value
Cell radius (r)	0.2 Km
System bandwidth (B)	3 GHz
Size of each data set (L)	100 Mbits
Gaussian white noise (σ^2)	-174 dBm/Hz
Path loss model	$148.1 + 37.6 \times \log_{10} r$, r (km): distance between BS and devices
Capacity of BS (C)	2000 data sets
Total number of data (F)	10000 data sets
The arriving rate (λ)	30 data sets/s
Energy consumption of wired transmission (e_2)	1J
Energy consumption of scheduling (e_1)	0.1J
Energy consumption of maintaining caching(e_3)	0.00001J

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2018.2794615, IEEE Transactions on Industrial Informatics

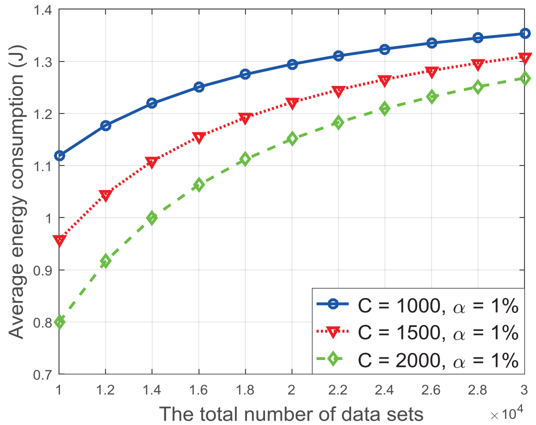


Fig. 5. The relationship between E and F.

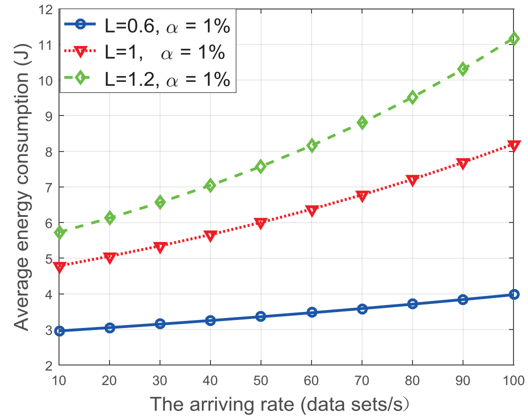


Fig. 8. The relationship between E and λ.

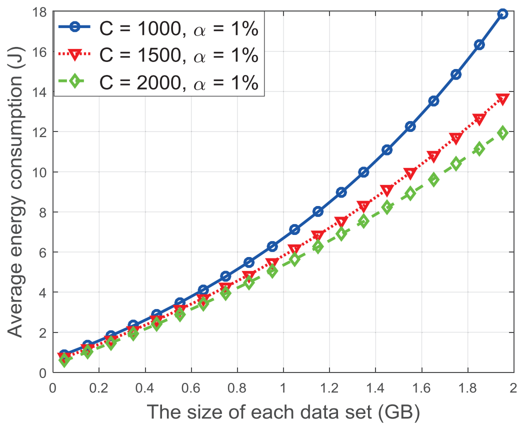


Fig. 6. The relationship between E and L.

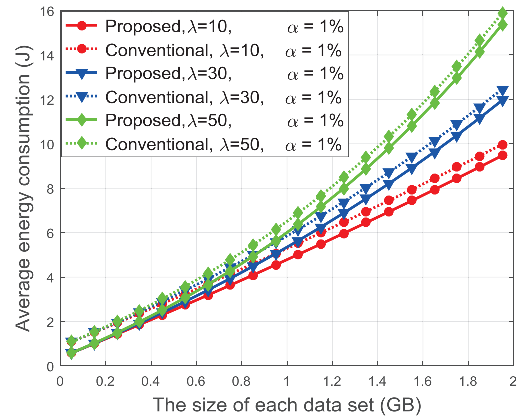


Fig. 9. The comparison of caching schemes.

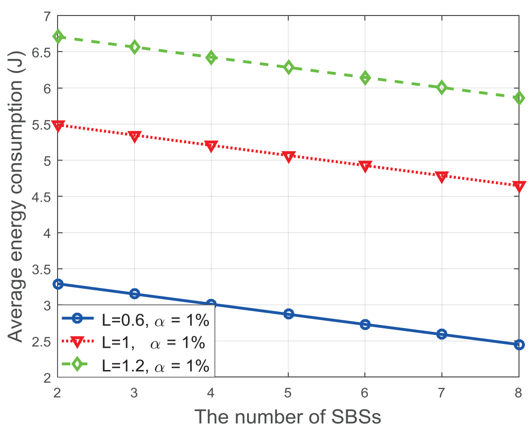


Fig. 7. The relationship between E and N.

B. The Impact of the Bandwidth

The optimal value of α is achieved, then in the simulation, we let $\alpha = 1\%$, and change the parameter of the bandwidth to discuss its impact. Fig. 4 shows that the average energy consumption decreases with the increase of the bandwidth. According to (24), we can easily find that the average energy consumption with the bandwidth is the inversely proportional relationship. But when the bandwidth increases to nearly 15GHz, the cut down of the average energy consumption followed by the augment of bandwidth is not obvious, that is to say, when the bandwidth is up to 15GHz, there is little significance to reduce the average energy consumption by the means of enhancing the bandwidth. This is determined by the property of the exponential function according to (2). So in the future 5G heterogeneous networks together with the cooperative caching scheme, the bandwidth is a very important parameter to the performance of the networks. However, when the bandwidth is up to 15GHz or even wider, it should seek another method to achieve the purpose of reducing the average energy consumption.

C. The Impact of the Total Number of Data Sets

We also let $\alpha = 1\%$ in the simulation, and change the parameter of the total number of data sets. We can notice that the total number of data sets increases, the average energy consumption would be correspondingly increased as shown in Fig. 5. The reason is that the capacity of the BSs is limited, when there are more data need to be requested, the more data need to be obtained from the servers. Then, the energy consumption of wired transmission would be increased, the average energy consumption would be increased too.

D. The Impact of the Size of Each Data Set

We let $\alpha = 1\%$ in the simulation, and change the parameter of the size of each data set. It is easy to understand when

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2018.2794615, IEEE Transactions on Industrial Informatics

the requested data contain more content, the more energy would be consumed. So the size of each data set increases, the average energy consumption would be correspondingly increased as shown in Fig. 6. But we can notice that with the size of each data set increases, the growth of the average energy consumption is at a very rapid rate. So it is better to cache smaller data set or cut bigger data set into smaller.

E. The Impact of the Number of Cooperative SBSs

In the simulation, we let the capacity of each BS is 2000 data sets and the $\alpha = 1\%$. We change the number of SBSs to analyze the impact of the numbers of the cooperative SBSs. As shown in Fig. 7, the average energy consumption decreases in the wake of the increasing of the numbers of cooperative SBSs. The more SBSs are clustered in a group, the more data can be cached, and the more energy consumption of scheduling data and maintaining caching would be consumed. However, the more data cached in the group of BSs, the less data need to be gotten from the servers. Obviously the energy consumption of wired transmission would be reduced. With the increasing of the numbers of the cooperative SBSs, the reduced energy consumption of wired transmission is more than the increased energy consumption of scheduling data and maintaining caching, so the average energy consumption would be reduced. It is better to cluster more SBSs as possible to achieve energy efficiency.

F. The Impact of the Arriving Rate

We set the capacity of each BS is 2000 data sets and $\alpha = 1\%$. We change the parameter of the arriving rate. Fig. 8 shows that the average energy consumption increases with the arriving rate improvement. The reason is that when there are more requests need to be handled, the power of wireless transmission would be increased to guarantee the quality of service, then energy consumption of wireless transmission increases, the average energy consumption correspondingly increases. When the arriving rate is higher enough, it is necessary to exploit new SBS to offload the burden to minimize the average energy consumption.

G. The Comparison of Caching Schemes

Fig. 9 shows that the performance of the caching scheme we proposed is more efficient than the conventional caching scheme. In the simulation, we can see that when the size of each data set and the arriving rate are both the same, the average energy consumption of the proposed space-reserved cooperative caching is lower than the conventional non-cooperative caching scheme. The reason is that in conventional method, when the data requested by devices are not cached in the local caching, the BS needs to get the data from the servers via backhaul links, leading to larger energy consumption of wired transmission. While in the proposed caching scheme, we utilize 1% of the capacity of each BS for the share and exchange of data. Though this would add extra energy consumption of scheduling, the increased energy consumption of scheduling is far less than the decreased energy consumption of wired transmission.

VI. Conclusion and Future Work

In this paper, we investigated the space-reserved cooperative caching scheme for IIoT in 5G heterogeneous networks. The problem was formulated with the objective of minimizing the average energy consumption in the network. Based on the formulation, we proved that the performance of the proposed scheme is more efficient than the conventional caching scheme. Moreover, comprehensive simulations reveal several findings of the space-reserved cooperative caching scheme. In the future, additional works are required. For instance, the popularity of data is a key parameter for the decision of caching, and the updating of caching is much rapid in the data area. It is very important to investigate the optimal strategy of the caching placement and replacement depending on the data popularity. Therefore, the strategy of placement and replacement of data is an interesting direction in the future.

References

[1] 5G Vision and Requirements, White Paper, *IMT-2020 (5G) Promotion Group*, May 2014.
[2] A. Brusakov, D. Borisov, et al, "Prospects for the development of IIOT technology in Russia," in *Proc. IEEE EIConRus*, 2017, pp. 1315-1317.
[3] S. Mumtaz, A. Alsohaily, Pang Z, et al, "Massive Internet of Things for Industrial Applications: Addressing Wireless IIoT Connectivity Challenges and Ecosystem Fragmentation," *IEEE Ind. Electron. Mag.*, vol. 11, no. 1, pp. 28-33, 2017.
[4] X. Wang, M. Chen, T. Taleb, A. Ksentini, and V. Leung, "Cache in The Air: Exploiting Content Caching and Delivery Techniques for 5G Systems," *IEEE Commun. Mag.*, vol. 52, no. 2, pp. 131-139, Feb. 2014.
[5] F. Pantisano, M. Bennis, W. Saad, and M. Debbah, "In-network caching and content placement in cooperative small cell networks," in *Proc. IEEE 5GU*, Nov. 2014, pp. 128-133.
[6] E. Bastug, M. Bennis, and M. Debbah, "Living on the edge: The role of proactive caching in 5G wireless networks," *IEEE Commun. Mag.*, vol. 52, no. 8, pp. 82-89, Aug. 2014.
[7] N. Golrezaei, A. F. Molisch, A. G. Dimakis, and G. Caire, "Femtocaching and device-to-device collaboration: A new architecture for wireless video distribution," *IEEE Commun. Mag.*, vol. 51, no. 4, pp. 142-149, Apr. 2013.
[8] Z. Hu, Z. Zheng, and T. Wang, "Game theoretic approaches for wireless proactive caching," *IEEE Commun. Mag.*, vol. 54, no. 8, pp. 37-43, 2016.
[9] G. Paschos, E. Bastug, and I. Land, "Wireless caching: Technical misconceptions and business barriers," *IEEE Commun. Mag.*, vol. 54, no. 8, pp.16-22, 2016.
[10] D. Liu, B. Chen, and C. Yang, "Caching at the wireless edge: Design aspects, challenges, and future directions," *IEEE Commun. Mag.*, vol.54, no. 9, pp. 22-28, 2016.
[11] W. Han, A. Liu, and V. Lau, "PHY-caching in 5G wireless networks: design and analysis," *IEEE Commun. Mag.*, vol. 54, no. 8, pp. 30-36, 2016.
[12] R. Tourani, S. Misra, and T. Mick, "IC-MCN: An Architecture for an Information-Centric Mobile Converged Network," *IEEE Commun. Mag.*, vol. 54, no. 9, pp.43-49, 2016.
[13] R. Huo , F. Yu, and T. Huang, "Software Defined Networking, Caching, and Computing for Green Wireless Networks," *IEEE Commun. Mag.*, vol. 54, no. 11, pp.185-193, 2016.
[14] H. Liu, Z. Chen, and L. Qian, "The three primary colors of mobile systems," *IEEE Commun. Mag.*, vol.54, no. 9, pp. 15-21, 2016.
[15] U. Niesen and M. A. Maddah-Ali, "Coded caching with nonuniform demands," in *Proc. IEEE Conf. Comput. Commun. Workshops (INFOCOM WKSHPS'14)*, 2014, pp. 221-226.
[16] M. Ji, A. M. Tulinoy, J. Llorcay, and G. Caire, "Order optimal coded caching-aided multicast under Zipf demand distributions," arXiv:1402.4576v1 [cs.IT], 2014.
[17] M. Ji, A. M. Tulinoy, J. Llorcay, and G. Caire, "Order optimal coded delivery and caching: Multiple groupcast index coding," arXiv:1402.4572v1 [cs.IT], 2014.
[18] K. Poularakis and L. Tassiulas, "Exploiting user mobility for wireless content delivery," in *Proc. IEEE ISIT*, 2013, pp. 1017-1021.

[19] Y. Guan, Y. Xiao, H. Feng, C.-C. Shen, and L. Cimini, “Mobicacher: Mobility-aware content caching in small-cell networks,” in *Proc. IEEE Global Commun. Conf. (Globecom)*, Dec 2014, pp. 4537-4542.

[20] K. Poularakis, G. Iosifidis, and L. Tassiulas, “Approximation algorithms for mobile data caching in small cell networks,” *IEEE Trans. Commun.*, vol. 62, no. 10, pp. 3665-3677, Oct. 2014.

[21] Y. Sun, Z. Chen, and H. Liu, “Delay Analysis and Optimization in Cache-enabled Multi-Cell Cooperative Networks,” in *Proc. IEEE Global Commun. Conf. (Globecom)*, Dec. 2016, pp. 1-7.

[22] F. Rezaei and B. H. Khalaj, “Stability, Rate, and Delay Analysis of Single Bottleneck Caching Networks,” *IEEE Trans. Commun.*, vol. 64, no. 1, pp. 300-313, 2016.

[23] C. Fang, F. Yu, and T. Huang, “A survey of energy-efficient caching in information-centric networking,” *IEEE Commun. Mag.*, vol. 52, no. 11, pp. 122-129, 2014.

[24] F. Rezaei, B. Khalaj, and M. Xiao, “Delay and stability analysis of caching in heterogeneous cellular networks,” in *Proc. IEEE ICT*, 2016, pp. 1-5.

[25] S. Mohamned, ElBamby, and B. Mehdi, “Content -Aware user clustering and caching in wireless small cell network,” in *Proc. IEEE ISWCS*, 2014, pp. 945-949.

[26] Z. Chen, J. Lee, and T. Quek, “Cluster-Centric Cache Utilization Design in Cooperative Small Cell Networks,” in *Proc. IEEE ICC*, May 2016, pp. 1-6.

[27] I. Keshavarzian, Z. Zeinalpour-Yazdi, and A. Tadaion, “A clustered caching placement in heterogeneous small cell networks with user mobility,” in *Proc. IEEE ISSPIT*, 2015, pp. 421-426.

[28] M. Tao, E. Chen, and H. Zhou, “Content-Centric Sparse Multicast Beamforming for Cache-Enabled Cloud RAN,” *IEEE Trans. Wireless Commun.*, vol. 15, no. 9, pp. 6118-6131, 2015.

[29] J. Zhang, X. Zhang, W. Wang, “Cache-Enabled Software Defined Heterogeneous Networks for Green and Flexible 5G Networks,” *IEEE Access*, vol. 4, pp. 3591-3604, 2016.

[30] K. Poularakis, G. Iosifidis, L. Tassiulas, “Joint caching and base station activation for green heterogeneous cellular networks,” in *Proc. IEEE ICC*, Jun. 2015, pp. 3364-3369.

[31] Y. Chiang, W. Liao, “ENCORE: An energy-aware multicell cooperation in heterogeneous networks with content caching,” in *Proc. IEEE ICCC*, May 2016, pp. 1-9.

[32] J. Gong, S. Zhou, Z. Zhou, Z. Niu, “Proactive Push with Energy Harvesting Based Small Cells in Heterogeneous Networks,” in *Proc. IEEE ICC*, Jun. 2015, pp. 25-30.

[33] F. Gabry, V. Bioglio, I. Land, “On Energy-Efficient Edge Caching in Heterogeneous Networks,” *IEEE J. Sel. Areas Commun.*, vol. 34, no. 12, pp. 3288 - 3298, 2016.

[34] S. Arai, Z. Fadlullah, T. Ngo, et al, “An efficient method for minimizing energy consumption of user equipment in storage-embedded heterogeneous networks,” *IEEE Wireless Commun.*, vol. 21, no. 4, pp:70-76, 2014.

[35] S. Fu, H. Wen, J. Wu and B. Wu, “Cross-Networks Energy Efficiency Tradeoff: From Wired Networks to Wireless Networks,” *IEEE Access*, vol. 5, pp. 15-26, 2017.

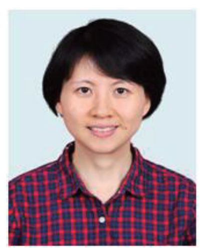
[36] S. Ross, “Introduction to Probability Models, Eleventh Edition,” *Academic Press, Inc.*, pp. 406-412, 2015.

[37] B. Chen, “Optimization Theory and Algorithm,” *Tsinghua University Press*, pp. 256-259, 2005.

Peng Duan received his B.E.degree in Communication Engineering from Shenyang University of Chemical Technology, China, in 2015. He is currently working toward his M.E. degree in Information and Communication Engineering in Chongqing University. His research interests include wireless transmission, caching, and IoT.

Yunjian Jia (M’06) received his B.S. degree from Nankai University, China, and his M.E. and Ph.D. degrees in En-gineering from Osaka University, Japan, in 1999, 2003 and 2006, respectively. From 2006 to 2012, he was a Researcher with Central Research Laboratory, Hitachi, Ltd., where he engaged in research and development on wireless networks, and contributed to LTE/LTE-Advanced standardization in 3GPP. He is now a professor at the College of Communication Engineering, Chongqing University, Chongqing, China. He is the author of more than 70 published papers, and 30 granted patents. His research interests include future radio access technologies, intelligent mobile networks, and IoT.

Dr. Jia has won several prizes from industry and academia including the IEEE Vehicular Technology Society Young Researcher Encouragement Award, the IEICE Paper Award, the Yoko-suka Research Park R&D Committee YRP Award, and the Top 50 Young Inventors of Hitachi. Moreover, he was a research fellowship award recipient of International Communication Foundation in 2004, and Telecommunications Advancement Foundation Japan in 2005.



Liang Liang received her B.Eng. and M.Eng. degrees from the Southwest University of Science and Technology (SWUST), China, in 2003 and 2006, respectively, and the Ph.D. degree in communication and information system from the University of Electronic Science and Technology of China (UESTC) in 2012. She is currently an associate professor in College of Communication Engineering, Chongqing University, Chongqing, China. Her research interests include wireless communication and optimization, green radio, and wireless sensor networks.

Jonathan Rodriguez (SM’13) received his Masters degree in Electronic and Electrical Engineering and Ph.D from the University of Surrey (UK), in 1998 and 2004 respectively. In 2005, he became a researcher at the Instituto de Telecomunicações (IT)-Portugal and Senior Researcher in 2008 where he established the 4TELL Research Group (http://www.av.it.pt/4TELL/) targeting next generation Mobile Systems with key interests on 5G, Security, and Antenna design. He has served as project coordinator for major international research projects, that includes Eureka LOOP and FP7 C2POWER, whilst serving as technical manager for FP7 COGEU and FP7 SALUS. He is currently leading the H2020-ETN SECRET project, a European Training Network on 5G communications. Since 2015, he became an Invited Associate Professor at the University of Aveiro (PT) and Honorary Visiting Researcher at the University of Bradford (UK). He is author of more than 400 scientific works, that includes 9 book editorials. His is IEEE Senior Member, Chartered Engineer (CEng) since 2013, and Fellow of the IET (2015). Since 2017. Since 2017, he is Professor of Mobile Communications at the University of South Wales (UK).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TII.2018.2794615, IEEE Transactions on Industrial Informatics

Kazi Mohammed Saidul Huq (M'16) received the bachelors degree in computer science and engineering from the Ahsanullah University of Science and Technology, Bangladesh, in 2003, the masters degree in electrical engineering from the Blekinge Institute of Technology, Sweden, in 2006, and the Ph.D. degree in electrical engineering from the University of Aveiro, Portugal, in 2014. He is a Senior Research Engineer with the Instituto de Telecomunicações, Aveiro, Portugal. His research activities include 5G paradigm, backhaul, D2D communication, energy-efficient wireless communication, radio resource management, and MAC layer scheduling. He has authored several publications, including papers in conferences and journals, and book chapters.

Guojun Li received the M.S., and Ph.D. degrees from Chongqing University of Posts and Telecommunications and Chongqing University in 2009 and 2012, respectively. He is currently an associate professor of Chongqing University of Posts and Telecommunications, China. His research efforts have been associated with statistical processing and detection of weak signal including physiological recordings. He has also worked in industry on the design and implementation of digital electronics and software in wireless sensor networks.